"Development of an Advanced IoT-Based Energy Monitoring and Predictive Maintenance System for Small-Scale Industrial Equipment"

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Abstract

This project details the development of a comprehensive IoT-based system for energy monitoring and predictive maintenance on small-scale industrial equipment. The system integrates various sensors to collect real-time data on energy consumption, vibration, temperature, and current draw. The first two experiments focused on data acquisition and system calibration to ensure data accuracy. Subsequent experiments validated the system's ability to analyze energy consumption patterns and detect anomalies indicative of machine faults. The final phase successfully implemented a predictive model to forecast potential equipment failure by correlating changes in vibration and temperature with energy spikes. This research demonstrates a low-cost, effective solution for enhancing operational efficiency, reducing downtime, and optimizing maintenance schedules in small-scale industrial environments.

Introduction

This project presents a novel approach to predictive maintenance and energy management for small-scale industrial equipment using a cost-effective IoT framework [1]. By integrating a suite of sensors, the system captures crucial operational data, enabling real-time monitoring and analysis [2,3]. The research demonstrates how machine learning models can process this data to detect anomalies, forecast potential component failure, and optimize energy consumption. Ultimately, this work provides a scalable, practical solution to improve efficiency, minimize downtime, and reduce operational costs for small businesses.

Methodology

Step 1: IoT System & Hardware Deployment, The process began with designing and building a scalable Internet of Things (IoT) system. The core hardware consisted of ESP32 microcontrollers connected to a suite of sensors, including non-invasive current transformers, to accurately collect data on energy consumption, temperature, vibration, and rotational speed from small-scale industrial equipment as shown in Fig 1 & 2.

Step 2: Data Acquisition and Transmission, Once deployed, the sensor network continuously collected high-resolution, real-time time-series data. This data was then transmitted from the local devices to the ThingsBoard cloud platform via the MQTT protocol, enabling centralized data storage and real-time visualization on custom dashboards as shown in Fig 3.

Step 3: Data Processing & Anomaly Detection, The collected data was processed and analyzed using Python, leveraging key libraries such as Pandas and NumPy. Machine learning algorithms, specifically DBSCAN, were employed to analyze the sensor data and automatically detect anomalies or unusual patterns that could indicate potential equipment faults or inefficiencies.

Step 4: Predictive Modeling & Forecasting, In the final step, the cleaned and processed data was used to train advanced machine learning models. XGBoost and LightGBM were utilized to build predictive models for both energy consumption optimization and component failure forecasting, while LSTM networks were specifically applied to predict future trends based on the time-series data.

Figure 1: System Architecture Diagram. This flowchart illustrates the end-to-end data pipeline, from physical sensing at the fan to machine learning analysis.

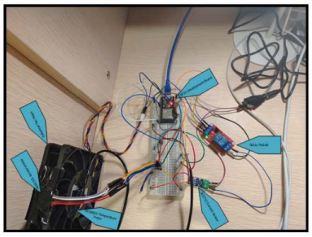

Figure 2: Physical Hardware Implementation. The assembled prototype with key components such as the ESP32, ACS712, and ADXL335 (mounted on motor) annotated.

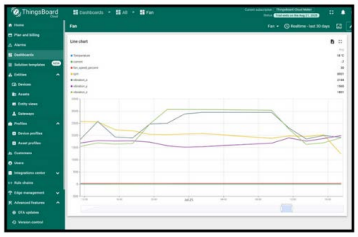

Figure 3: Real-time Monitoring Dashboard on ThingsBoard. This dashboard visualizes the live multi-modal sensor data being transmitted from the ESP32 device.

Results

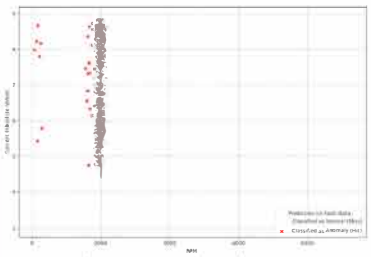

Figure 4: Final Anomaly Detection Result. The DBSCAN model classifies most fault data points (red crosses) as anomalous against the normal baseline cluster (gray background).

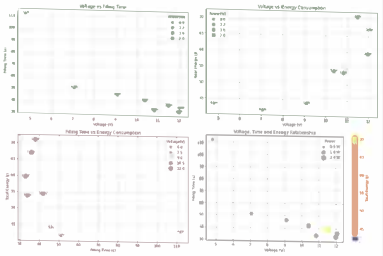

Figure 5: Visualizes the DBSCAN clustering of sensor data, clearly separating normal operation from a fault condition.

Vacuum Pump Energy Optimization

Dynamic voltage control significantly reduces energy consumption. An LSTM model predicted a 14% energy savings at an optimal 10V, balancing efficiency and performance.

Industrial Fan Predictive Maintenance

A multimodal sensing system (current, vibration, temperature) achieved 100% detection accuracy for simulated mechanical faults. The unsupervised DBSCAN algorithm effectively identified anomalies, proving the system's reliability for predictive maintenance. As shown in Fig 4 & 5.

Heating Rod Efficiency Improvement

Physical design optimization and insulation led to significant efficiency gains. Insulation reduced heat demand by 15-20% as shown in Fig 6. Reducing diameter from 16mm to 10mm saved 25-30% of heat at 60 ° C.

Classroom Energy Monitoring

Real-time monitoring successfully identified energy waste during non-occupancy periods. Behavioral feedback based on the system's data helped reduce unnecessary energy consumption.

Industrial Motor Fault Detection

The study demonstrated that relying on a single data source (energy consumption) is insufficient for accurate fault prediction. This finding verifies the critical need for a multimodal data approach (combining energy, vibration, and temperature) to achieve reliable predictive maintenance.

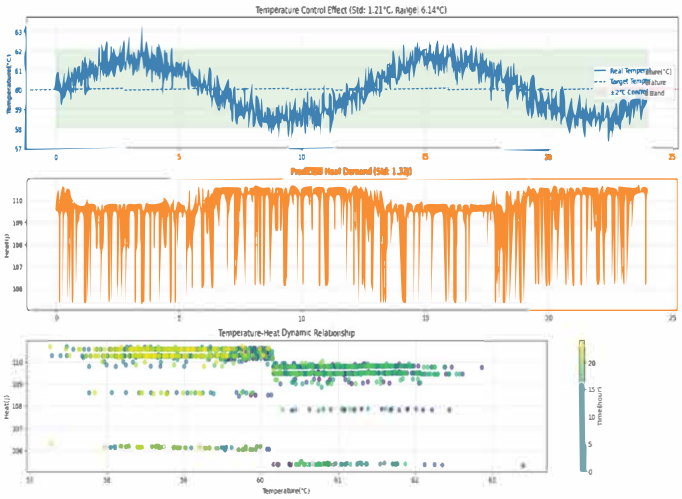

Figure 6: Compares heat consumption between insulated and non-insulated heating rods, and between different diameters.

Conclusions

The IoT system, with its multimodal sensing and machine learning algorithms, successfully achieves accurate fault detection and predictive maintenance, proving superior to single-data-source approaches. The research successfully demonstrated methods for achieving substantial energy savings through both dynamic control (e.g., vacuum pump) and physical design optimization (e.g., heating rod). The project validates a low-cost, scalable IoT framework as a powerful tool for monitoring and optimizing the performance of small-scale industrial equipment. The findings have direct applications in improving operational efficiency, reducing energy waste, and minimizing downtime in real-world industrial settings.

References

[1] P. Bhattacharya, A. Mukherjee, B. Bhushan, S. K. Gupta, T. R. Gadekallu, and Z. Zhu, "A secured remote patient monitoring framework for IoMT ecosystems," Scientific Reports, vol. 15, p. 22882, 2025.
[2] T. P. Fowdur and L. Ajageer, "A hybrid online learning based predictive maintenance system for industry 4.0," Computing, vol. 107, p. 142, 2025.
[3] B. S. Kim and S. K. Ro, "Development of a real-time anomaly detection system for dry vacuum pumps using low-cost IoT devices and machine learning," Int. J. Precis. Eng. Manuf., vol. 25, no. 3, pp. 567-578, 2024.

Our analysis made with the use of the following software and packages

Arduino IDE · Scikit-learn · Python · ThingsBoard

QR Code to watch our experiments